MODELING EDUCATIONAL TECHNOLOGY ACCEPTANCE AND SATISFACTION

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Abstract

This paper examines various extensions of the Unified Theory of Acceptance and Use of Technology (UTAUT) and related frameworks from a theoretical and empirical point of view. A brief discussion of the relevant literature – from a multidisciplinary perspective – explains why it is important to bridge the different fields that are involved: educational science, statistical computing, and technology acceptance research.

The theoretical contribution of the paper consists of substantial extensions/improvements of the UTAUT which are embedded within the theoretical paradigm of social constructivism. It is argued that the usability aspects of e-learning systems cannot be treated independently from their impact on learning behavior and the pedagogical setting in which they are implemented.

The empirical evidence is based on our on-going efforts to implement and improve the Compendium Platform which features Reproducible Computing Technology for the purpose of Statistics Education. Based on new empirical data from an experimental, undergraduate statistics course we are now able to provide strong support for a newly proposed Educational Technology Acceptance & Satisfaction Model (ETAS-M). The empirical analysis is based on a methodological approach which allows us to substantially improve the predictive performance of the model through a transformation technique that derives optimal weights for the items of the endogenous variable.

Keywords - technology acceptance, learning outcomes, learning satisfaction, social constructivism

1 INTRODUCTION

In an attempt to define a unified view on user acceptance of information technology, Venkatesh et al. [4] proposed the so-called Unified Theory of Acceptance and Use of Technology (UTAUT) which serves as a starting point for the analysis of this paper. Our research (which is based on the implementation of a novel technology in an experimental statistics course) clearly provides evidence for a revised version of the model, in which the missing links with important pedagogical components that are related to the input and the output side of the original UTAUT, are explicitly taken into account.

The basic concepts of UTAUT are loosely depicted in Fig. 1. Fig. 1 assumes that there are four constructs that affect user acceptance and usage behavior: Performance Expectancy, Facilitating Conditions, Effort Expectancy, and Social Influences. In addition, four moderator variables are defined which affect the relationships between the mentioned constructs, and Intention or Actual Use.

Fig. 1 is not an exact copy of UTAUT as it was originally presented. Rather, it represents the core components of UTAUT that are of interest in this paper and their inter-relationships. It is also illustrated that there are (at least) two missing components which have an important relationship with technology perception and use. The model in Fig. 1 differs from the original depiction of Venkatesh et al. [4] in the following ways:

- The component "Social Influence" was omitted because the three associated constructs (Subjective Norm, Social Factors, and Image) are not relevant within our research context:
    - Subjective Norm refers to "the person's perception that most people who are important to him think he should or should not perform the behavior in question" [4] and does not

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contribute to the prediction of technology acceptance or use. Every student that participated in our experimental statistics course was required to use the system by the educator. Students who did not consistently use the software and participate in the entire course (because of health-related issues) were excluded from the database and are therefore not part of the analysis. Note that for this reason the moderating variable “Voluntariness of Use” is also not included in Fig. 1.

  - Social Factors are “the individual's internalization of the reference group's subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations” which are limited to voluntary, interpersonal reasons. In our educational setting however, students' behavior is affected by the social interactions that are supported by the Computer-Assisted Learning (CAL) activities which are featured in the Statistical Learning Environment (SLE). CAL activities are a function of the pedagogical paradigm that provided the foundation for the design of the course and the SLE – hence, they cannot be the result of interpersonal agreements. Instead, we argue that pedagogical factors should be introduced in order to explain technology acceptance and use. Since our experimental statistics course is embedded in the pedagogical paradigm of social constructivism it is clear that the “relevant social factors” are just a subset of the “Pedagogical Paradigm”.
  - The Image construct is defined as “the degree to which use of an innovation is perceived to enhance one's image or status in one's social system” and is unlikely to play any important role in undergraduate statistics learning. In addition, our experimental statistics course is situated in an academic business school where students are not particularly fond of math-related courses.

- The original UTAUT makes an explicit distinction between age and experience. It is unrealistic to assume – at least in an educational setting – that it would be possible to differentiate between age-effects and experience-effects on technology acceptance or use. In the experimental statistics course we have ordinary (bachelor) students and students from the preparatory program. These so-called prep-students are older than bachelor students and already have obtained a (professional) bachelor degree (hence, they are more experienced). The reason why they are in a prep-program is that they need to study methodological courses (such as statistics) and economics before they are admitted to the academic master program. The research that is presented in this paper makes no distinction between age and experience: a student is either in the prep-program (c.q. is older and has more experience) or in the bachelor program.
- An endogenous variable in the original UTAUT is Actual Use. In addition, it is assumed that the Performance Expectancy constructs (Relative Advantage, Usefulness, etc...) and the Effort Expectancy constructs (such as Ease of Use) can only affect Actual Use through the construct of Intention to Use which is typically a construct that is derived from a questionnaire that is also used to measure the exogenous constructs. This seems to be somewhat restrictive because of two reasons:
  - Performance Expectancy and Effort Expectancy can have a direct effect on Actual Use – introducing a go-between construct (Intention to Use) only decreases the variability in the exogenous variable that is used to predict Actual Use (this results in an increased variance of the estimated parameters). From a statistical point of view this does not make sense at all.
  - Intention to Use is often used as the endogenous variable because there is no information available about Actual Use. In this research however, we have accurate and objectively measured data about Actual Use available. Although usage of the SLE is mandatory (students have to complete their assignments with the new technology), a student could choose to exploit the SLE more extensively by doing extra statistical reproductions or sending more or less feedback messages. This behavior was recorded and used in our model.
- The original UTAUT does not mention the ultimate goal of using technology. In the case of education, the ultimate goal is to learn, or to gain true (as opposed to “rote”) understanding of statistical concepts. These learning outcomes can be objectively measured by exam questions which attempt to measure understanding rather than memorization. In fact, the use of

technology should lead to better learning outcomes, and it is therefore important to estimate the impact of UTAUT components on Exam Scores.

The UTAUT model is believed to be an incomplete description of the SLE because there are no connections with the concepts of Pedagogical Paradigm and Exam Scores (measuring learning outcomes). In addition, it is claimed (in UTAUT) that Facilitating Conditions have a direct impact of Actual Use and that gender is not a moderator. The empirical results (to be shown below) will falsify this assumption. Furthermore, it will be shown that the direct effect of UTAUT components (on Exam Scores and Actual Use) can be measured, and that the impact of Intention to Use (on Actual Use or Exam Scores) can only be measured if it is mediated through experience and age-effects.

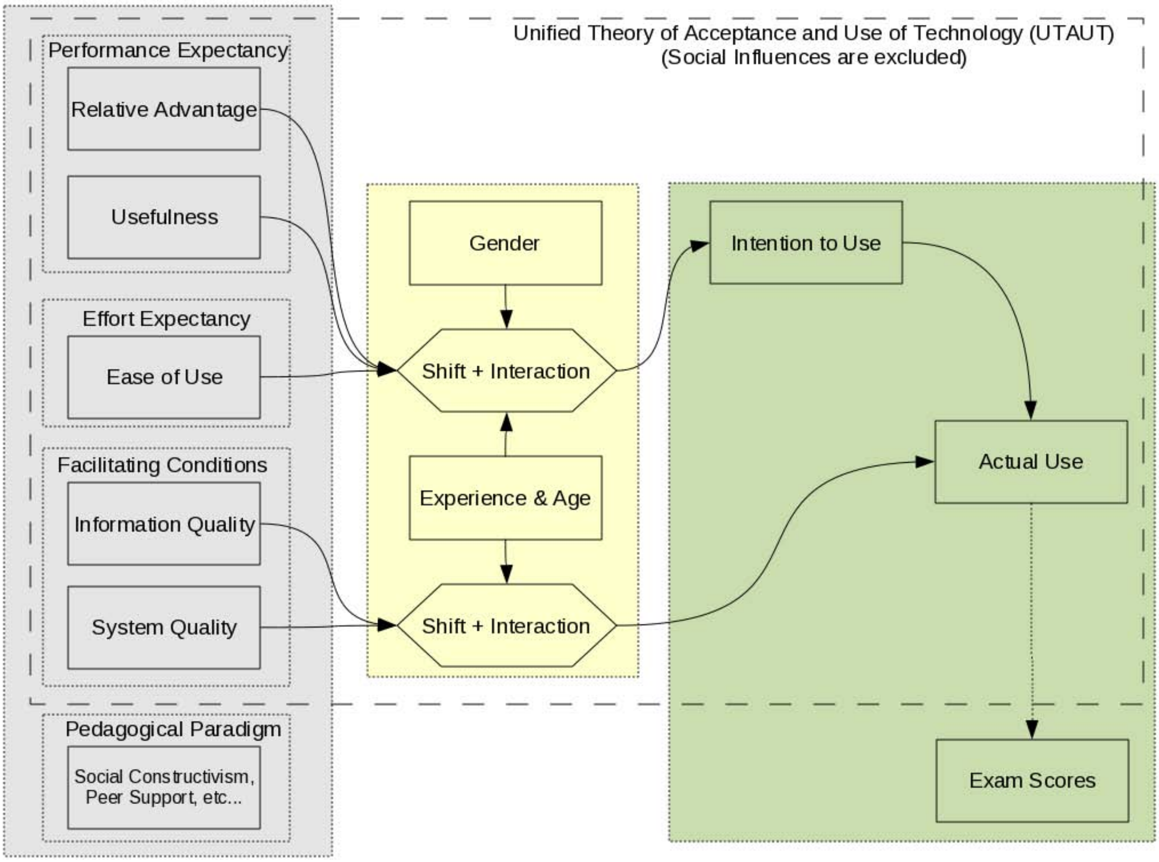

Figure 1: UTAUT and missing Pedagogical Components

2 DATA & METHODOLOGICAL ASPECTS

The data were collected during the fall/winter semester 2008 in an experimental, undergraduate statistics course with an emphasis on socially constructivist, CAL activities. The key-aspects of the SLE (including pedagogical and technical properties) are explained in detail in [6]. The point that makes this course well-suited to investigate the UTAUT is the fact that the newly developed Reproducible Computing Technology [7] was introduced in the SLE in such a way that students could engage in interactive peer review/teaching/assessment activities without the hassle of the many technicalities that are often associated with reproducing empirical results.

The data set only contains those students for whom the technology was unknown before the start of the semester – all students who failed to pass the course in the previous year were eliminated from the database. In addition, great care was taken to remove students with incomplete, or inaccurate data. The remaining student population consists of 169 students who actively took part in all learning processes and completed a (difficult) test at the end of the semester in which the questions were intended to measure (true) conceptual understanding rather than rote memorization [6]. The student population under study is categorized by four so-called cohorts (female bachelor, male bachelor, female preparatory, and male preparatory). It has been well established that these cohorts are relevant for the purpose of statistical analysis [5], [6].

The UTAUT constructs have been measured by the use of the Computer System Usability Questionnaire as defined by Lewis [1] and extended by Poelmans et al. [3]. The construct of “Social Constructivism” measures the degree in which students feel that they engage in socially constructivist learning (through computer-assisted peer teaching/assessment) during the semester. This construct was measured by the so-called Constructivist On-Line Learning Environment Survey (COLLES) as implemented in the Virtual Learning Environment Moodle [2] (questions 17, 19, 21, and 23). The construct of “Peer Support” was measured with the same survey (based on questions 33, 35, 37, 39) and represents the degree in which students feel that they receive encouragements and praises from peers (within the context of reviews). Both constructs are clearly related to the social aspects of the pedagogical paradigm in which the SLE is embedded – they are however, fundamentally different from the Social Factors that are defined in the original UTAUT.

The measurements of Actual Use were obtained by analyzing the logfiles of the SLE which contains detailed information about all statistical computations, including the computational archives created thereof, and the reproduction/reuse of computations in the context of peer review activities. The construct Actual Use contains three components which have been shown to be relevant in previous research [6]:

- the number of meaningful, submitted feedback messages which are based on reproducible computations that were archived in the online repository
- the number of meaningful, feedback messages that were received about one's assignment paper
- the number of reproducible, statistical computations that were generated and archived

The design of the test at the end of the semester (labeled “Exam Scores”) was based on experiences from previous research [6]. Even though all the questions were designed with great care, there are a number of reasons why the total score of such a test may not be fully adequate for measuring the relationships between any number of co-factors and the learning outcomes that are estimated by the test. For this reason, a mathematical model was created which allows us to define the weights that are attributed to each question in such a way that the determination coefficient (the so-called R-squared) of the relationship under investigation is maximized [5]. Since this methodology does not only apply to exam scores – but any endogenous variable which consists of multiple items for which no objective weights exist – we used this approach for all estimated relationships, including those that relate to the prediction of Intention and Actual Use. The obvious advantage of such a methodological approach is that there is no need to rely on traditional models in which the constructs (of the endogenous variable) are represented by arbitrarily attributed weights. None, of the empirical findings that explain Actual Use or Exam Scores (as presented in the next section) could have been obtained without the optimal transformation technique.

3 ANALYSIS

Table 1 displays the effects of five UTAUT components and two constructs from the Pedagogical Paradigm component on Intention to Use. Each column represents a different type of model in which the effects of the cohorts are taken into account in various ways. The “none” column represents the results under the assumption that the student population is homogeneous (c.q. the relationship is computed with fixed parameters for all students simultaneously). In the last column (labeled “all”) the relationships have been computed, taking into account all cohort-effects of the student population (female-bachelor, male-bachelor, female-preparatory, male-preparatory). More precisely, the models that are represented in the last column contain the following additional parameters:

- A shift effects for gender and a shift effect for age & experience (bachelor vs. preparatory). Note that a “shift effect” simply represents the change in the overall level of the endogenous variable (depending on the value of the binary indicator variable).
- An interaction between each parameter of the exogenous variables (displayed in the rows) and gender.
- An interaction between each parameter of the exogenous variables with age & experience.

In other words, these models have different constant terms and causal parameters for each of the four cohorts. The other columns represent models which have only a subset of the additional, cohort-related parameters. For instance, the "gender" column contains a shift and interaction effect that refers to gender, and the "gender*" column only contains the interaction effect (without shift). A similar definition applies the the "age+exp" and "age+exp*" columns.

	Intention to Use					
R^2	**none**	**age+exp.**	**age+exp.***	**gender**	**gender***	**all**
Relative Advantage	40.89%	42.75%	42.58%	41.87%	41.60%	44.71%
System Quality	43.81%	50.55%	49.94%	47.93%	47.92%	58.94%
Information Quality	41.75%	44.00%	42.01%	42.95%	42.90%	47.52%
Ease of Use	36.80%	41.93%	39.95%	39.25%	39.20%	46.00%
Usefulness	30.30%	31.10%	30.61%	32.81%	32.74%	34.66%
Intention	NA	NA	NA	NA	NA	NA
Social Constructivism	59.47%	60.61%	60.30%	60.98%	60.90%	62.71%
Peer Support	19.55%	29.65%	28.50%	24.74%	23.86%	35.45%
p-value						
Relative Advantage	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
System Quality	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Information Quality	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Ease of Use	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Usefulness	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Intention	NA	NA	NA	NA	NA	NA
Social Constructivism	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Peer Support	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 1: Effects of UTAUT components on Intention to Use

Table 1 clearly demonstrates that all UTAUT components have a significant R^2 (upper panel) values which represent the effect of the row variable on Intention to Use: the p-values of the corresponding F-tests are displayed in the lower panel of the table. It is obvious that all relationships are significant – the cohort does not really matter. This result implies that UTAUT represents a robust theory that applies to students from different cohorts.

Table 2 shows how UTAUT components affect actual use of software (within the context of constructivist, computer-assisted learning activities). The results are striking and substantially different from Table 1 and the predictions that are made by the traditional UTAUT:

- The relationships between UTAUT components and actual use cannot be computed without explicitly taking into account cohort effects (see "none" column). The only exception is the effect of Ease of Use which is significant at the 1% type I error level.
- There is no gender-related shift or interaction effect for the relationships between the exogenous components and actually observed use of technology. Again, the exception to this rule is Ease of Use for which a significant gender effect was found – this may have implications for the design and implementation of CAL technology. The effect of Social Constructivism is only significant (at the 5% type I error level) when the shift is neglected.
- There are strong population effects (with and without shift) for the relationship between all exogenous components and actual use of technology.

These findings are of utmost importance because the effects of gender and age/experience are not incorporated in the traditional UTAUT. Moreover, these effects, play a crucial role in psychological and pedagogical theories and have been used to explain learning processes in general and CAL-effects in particular. We therefore conclude that Social Constructivism is a valuable explanatory component and should be included in the Educational Technology Acceptance Model (ETA-M) that we propose at the end of this paper.

The estimated effects in Tables 1 and 2 differ substantially and therefore clearly illustrate the fact that Intention to Use behaves differently than Actual Use. More importantly, in order to explain Actual Use (based on exogenous UTAUT variables) one must take into account the shift and interaction effects of age/experience and gender. In particular, this is also the case for Intention to Use: it's effect on Actual

Use is only significant when the Age/Experience effect is explicitly taken into account – unlike what is suggested in the UTAUT. In this sense, there is no need for a go-between variable to explain Actual Use. Moreover, one might question if it is necessary to use Intention to Use as a predictor because Table 2 clearly suggests that Actual Use can be well-explained by estimating the direct effects of the exogenous UTAUT variables and the "Pedagogical Paradigm".

Also note that the fact that the Intention to Use construct can be predicted by the other UTAUT constructs (see Table 1), could be a reflection of the internal consistency of reported information which is provided by students – it does not necessarily mean that Intention to Use is a necessary predictor for Actual Use. We may conclude that Intention to Use is an interesting endogenous variable, but redundant as exogenous variable.

	Actual Use					
R^2	none	age+exp.	age+exp.*	gender	gender*	all
Relative Advantage	1.89%	21.28%	12.83%	2.84%	2.80%	22.39%
System Quality	7.26%	25.91%	22.45%	15.72%	15.19%	36.76%
Information Quality	4.23%	18.93%	11.67%	4.95%	4.95%	23.61%
Ease of Use	7.84%	22.51%	15.27%	19.04%	18.97%	33.17%
Usefulness	2.59%	17.95%	11.96%	3.24%	3.23%	20.39%
Intention	1.26%	19.10%	15.27%	1.36%	1.29%	21.45%
Social Constructivism	5.58%	21.66%	16.09%	9.27%	9.15%	25.40%
Peer Support	1.20%	17.81%	15.37%	3.15%	2.36%	23.47%
p-value						
Relative Advantage	0.2053	0.0000	0.0001	0.4488	0.3218	0.0000
System Quality	0.3511	0.0026	0.0121	0.2762	0.2663	0.0319
Information Quality	0.2125	0.0004	0.0284	0.6950	0.6065	0.0064
Ease of Use	0.0092	0.0000	0.0007	0.0001	0.0000	0.0000
Usefulness	0.2267	0.0000	0.0019	0.6130	0.4954	0.0009
Intention	0.3494	0.0000	0.0000	0.8137	0.7097	0.0000
Social Constructivism	0.0503	0.0000	0.0004	0.0711	0.0479	0.0003
Peer Support	0.7384	0.0002	0.0007	0.8172	0.8674	0.0010

Table 2: Effects of UTAUT components on Objectively Measured, Constructivist, CAL Activities

Table 3 summarizes the effects of UTAUT components on objectively measured Exam Scores. As explained in the methodological section, all endogenous variables (in Tables 1, 2, and 3) have been subjected to the methodology of applying optimal weights (to the items of the endogenous variable). This implies that "bad/inappropriate exam questions" have a lower weight whereas "good exam questions" have a more weight. In this sense, we can determine if there are any exogenous components that truly lead to better understanding of statistical concepts (hence, we need to be concerned about the biases that would be induced by bad exam questions because these effects are automatically reduced). The results from our analysis are surprising in several ways:

- Intention to Use and Social Constructivism, both have a significant impact on Exam Scores if the student population is assumed to be homogeneous. All other UTAUT components have no measurable effect on exam scores, except if cohort-effects are taken into account.
- Most exogenous components have a significant impact on exam scores if population-effects are accounted for - the only exception is System Quality.
- System Quality has an effect on exam scores if the gender-effect is taken into account. In other words, the System Quality has a significant effect (on exam scores) which is different for male and female students. This is consistent with the observation that many scholarly studies have demonstrated gender-related differences in attitudes towards computing, and computing anxiety which is closely related to System Quality.

	Optimally Weighted Exam Scores					
R^2	none	age+exp.	age+exp.*	gender	gender*	all
Relative Advantage	3.31%	10.14%	6.54%	3.97%	3.97%	12.71%
System Quality	7.22%	14.69%	11.86%	26.08%	25.87%	39.22%
Information Quality	4.53%	16.21%	15.34%	5.57%	5.52%	19.10%
Ease of Use	3.96%	10.65%	9.25%	8.38%	7.05%	20.44%
Usefulness	3.23%	15.75%	13.11%	4.52%	4.05%	17.56%
Intention	4.31%	13.27%	12.00%	5.49%	5.40%	15.82%
Social Constructivism	6.76%	13.65%	12.12%	8.30%	8.16%	17.27%
Peer Support	1.50%	9.12%	7.83%	2.89%	2.54%	11.13%
p-value						
Relative Advantage	0.0614	0.0035	0.0249	0.2475	0.1540	0.0151
System Quality	0.3568	0.3681	0.6041	0.0023	0.0017	0.0105
Information Quality	0.1787	0.0027	0.0026	0.5993	0.5129	0.0619
Ease of Use	0.1550	0.0320	0.0452	0.1148	0.1547	0.0069
Usefulness	0.1424	0.0002	0.0008	0.3737	0.3415	0.0058
Intention	0.0259	0.0003	0.0003	0.0982	0.0571	0.0019
Social Constructivism	0.0210	0.0046	0.0070	11.9500	0.0852	0.0384
Peer Support	0.6473	0.0773	0.1026	0.8538	0.8390	0.4152

Table 3: Effects of UTAUT components on Objectively Measured, and Optimally Weighted Exam Scores

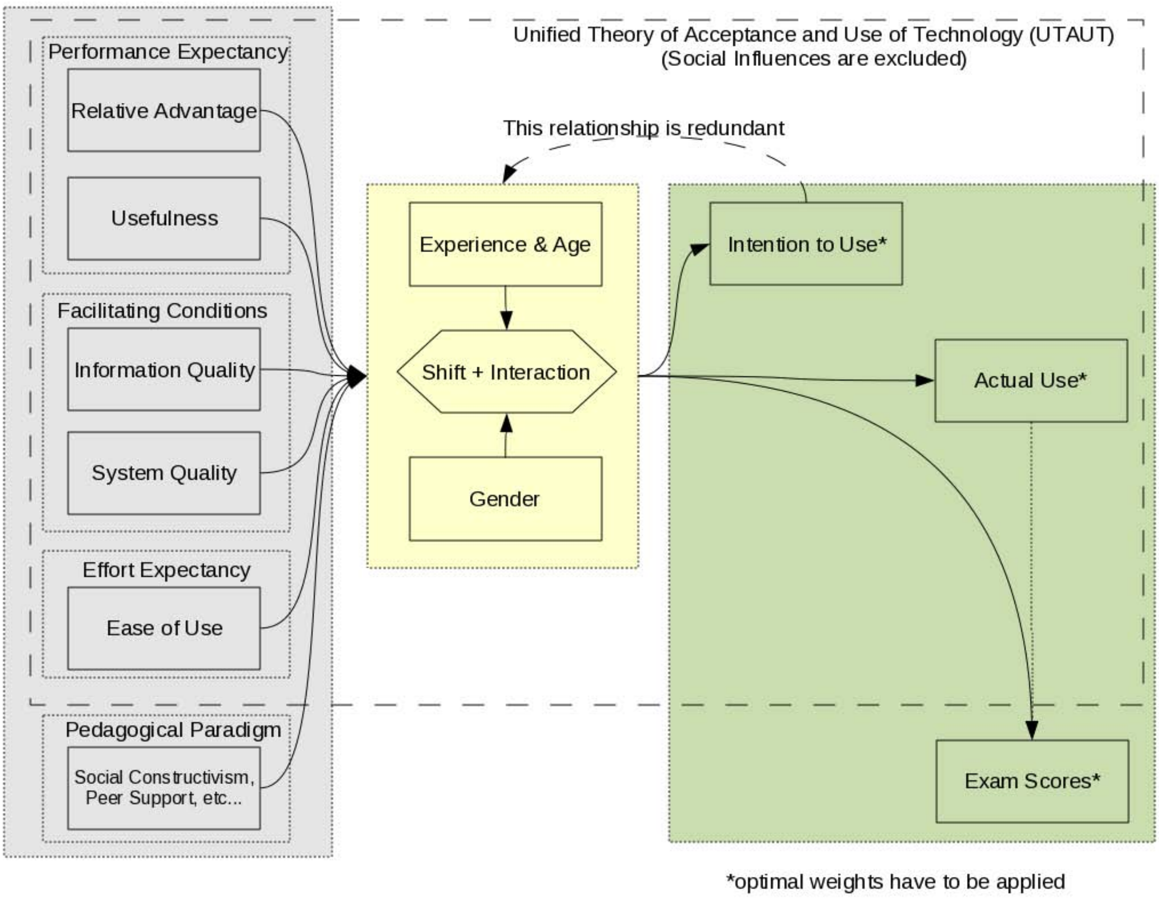

Figure 2: proposed Educational Technology Acceptance & Satisfaction Model (ETAS-M)

If we compare Tables 2 and 3 it is obvious that effect of System Quality depends on age/experience-interactions (for Actual Use) and gender-effects (for Exam Scores). At first sight, this might look like an inconsistency if one assumes that the use of CAL activities automatically lead to non-rote learning (and hence favorable exam results).

There are however, several psychological explanations for this phenomenon. One of the more reasonable explanations is that students who use the software do so for different reasons and with different degrees of efficiency. Overall, students from the prep-program are more experienced in performing practical, computer-based tasks. Therefore, they will quickly adopt and use novel technologies that are introduced in their learning environment. This however does not necessarily imply that all students use the technology with the same degree of learning efficiency. Female students may, for instance, feel less confident in using technology and – therefore – be more sensitive to the overall System Quality of the learning technology.

The effects of Tables 1, 2, and 3 have been summarized in Fig. 2 which illustrates our proposition for a new Educational Technology Acceptance & Satisfaction Model (ETAS-M) which incorporates (but is not limited to) the UTAUT components that affect learning outcomes if gender and/or age/experience effects are taken into account.

4 CONCLUSIONS

Our research suggests that the proposed ETAS-M is well-suited to explain technology acceptance for the purpose of learning environments because it explicitly takes into account the pedagogical paradigm in which it is embedded and because it allows us to predict actual use and learning outcomes. All ETAS-M relationships are mediated through gender and/or age/experience effects with shifts and interactions. The endogenous variables (Actual Use and Exam Scores in particular) need to be transformed in order to avoid statistical obfuscation of the estimated parameters when arbitrary (non-optimal) weights are used.

Both corresponding authors, gladly accept comments or suggestions about the research and the model which is presented in this paper.

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